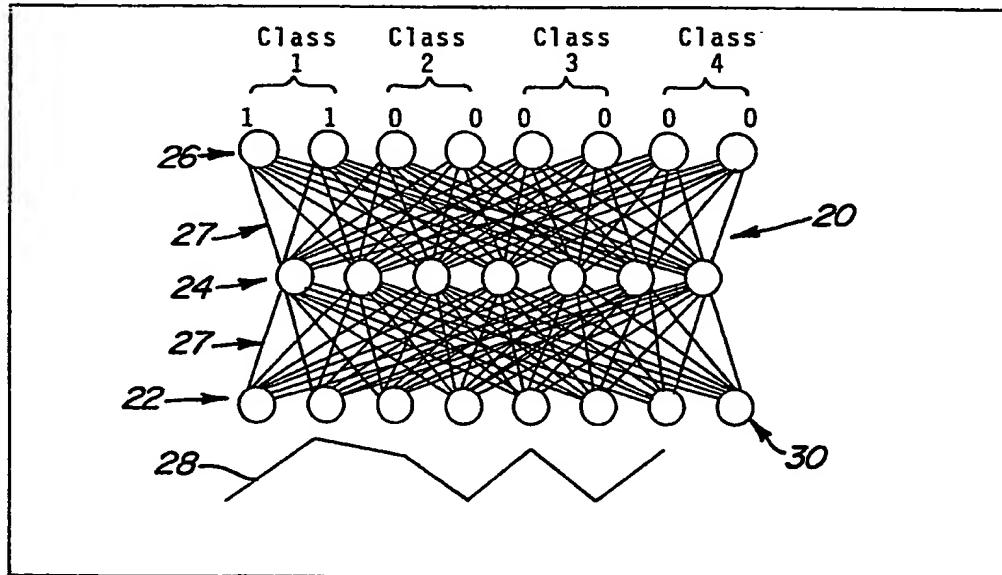




## INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

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## (54) Title: ADAPTIVE NETWORK FOR CLASSIFYING TIME-VARYING DATA



## (57) Abstract

An information processor (20) for classifying a set of two-dimensional data. The data represents information from at least two domains. The processor (20) utilizes a neural network architecture having at least  $N + 1$  input neurons (22), where  $N$  is the number of values in the first domain. The network (22) is trained to produce an output state that classifies a plurality of input signals belonging to a particular class. In the preferred embodiment the second domain is time.

## DESIGNATIONS OF "DE"

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## ADAPTIVE NETWORK FOR CLASSIFYING TIME-VARYING DATA

1                   Background of the Invention1. Technical Field

5                   This invention relates to information processors and, more particularly, to a method and apparatus for classifying time varying data.

2. Discussion

10                  Classifying of complex time-varying data poses a number of difficult problems for conventional information processors. The task of classification typically involves recognizing patterns typical of known classes from large amounts of two-dimensional data. Where the patterns to be recognized have subtle variations between the known classes, traditional classifiers often fail to correctly distinguish between 15 the classes. This is due, in part, to the strong assumptions which must be made concerning the underlying distributions of the input data. Algorithms must then be developed to extract these features and to match known features with the input features for 20 classification.

25                  The success of the classifier is dependent on the correctness of these underlying assumptions. Many problems are not susceptible to explicit assumptions in algorithms, due to the subtlety of the patterns involved, as well as the wide variations of such patterns within each class. A further disadvantage

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1 with traditional classifiers is the extensive preprocessing normally required and the extensive time required to develop the algorithm and software to accomplish the pattern matching. Examples of such  
5 classification problems include classifying time varying signals from various sources such as speech, image data, radar, sonar, etc. Also, conventional information processor are generally not fault tolerant, and cannot handle certain variations in the input  
10 signals such as changes in the orientation of a visual pattern, or differences in speakers, in the case of speech recognition.

In recent years it has been realized that conventional Von Neumann computers, which operate serially, bear little resemblance to the parallel processing that takes place in biological systems such as the brain. It is not surprising, therefore, that conventional information classification techniques should fail to adequately perform the pattern  
15 recognition tasks performed by humans. Consequently, new methods based on neural models of the brain are being developed to perform perceptual tasks. These systems are known variously as neural networks, neuromorphic systems, learning machines, parallel  
20 distributed processors, self-organizing systems, or adaptive logic systems. Whatever the name, these models utilize numerous nonlinear computational elements operating in parallel and arranged in patterns reminiscent of biological neural networks. Each  
25 computational element or "neuron" is connected via weights or "synapses" that typically are adapted during training to improve performance. Thus, these systems exhibit self-learning by changing their synaptic weights until the correct output is achieved in  
30 response to a particular input. Once trained, neural  
35

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1 nets are capable of recognizing a pattern and producing  
a desired output even where the input is incomplete or  
hidden in background noise. Also, neural nets exhibit  
greater robustness, or fault tolerance, than Von  
5 Neumann sequential computers because there are many  
more processing nodes, each with primarily local  
connections. Damage to a few nodes or links need not  
impair overall performance significantly.

10 There are a wide variety of neural net models  
utilizing various topologies, neuron characteristics,  
and training, or learning, algorithms. Learning  
algorithms specify an internal set of weights and  
indicate how weights should be adapted during use, or  
training, to improve performance. By way of  
15 illustration, some of these neural net models include  
the Perceptron, described in U.S. Patent No. 3,287,649  
issued to F. Rosenblatt; the Hopfield Net, described in  
U.S. Patent Nos. 4,660,166 and 4,719,591 issued to J.  
Hopfield; the Hamming Net and Kohohonen self-organizing  
20 maps, described in R. Lippman, "An Introduction to  
Computing with Neural Nets", IEEE ASSP Magazine, April  
1987, pages 4-22; and "The Generalized Delta Rule for  
Multilayered Perceptrons", described in Rumelhart,  
Hinton, and Williams, "Learning Internal  
25 Representations by Error Propagation", in D. E.  
Rumelhart and J. L. McClelland (Eds.), Parallel  
Distributed Processing: Explorations in the  
Microstructure of Cognition. Vol. 1: Foundation. MIT  
Press (1986).

30 While each of these neural net models achieve  
varying degrees of success at the particular task to  
which it is best suited, a number of difficulties in  
classifying time-varying data still are encountered  
when using neural network processors. For example,  
35 where the time-varying data is complex and involves

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1 large quantities of data, a major problem is in  
developing a technique for representing the data to the  
neural network for processing. For example, in  
5 classifying radar or sonar doppler time signatures from  
objects, the minimum amount of data required to  
adequately represent classifications may involve, for  
example, fifty time slices of sixteen frequency bands  
of the doppler data. One way to present this data to a  
10 neural net processor would be to utilize a neural  
network with 800 (50 + 16) input neurons and to present  
each of the 800 input neurons with one sample of  
doppler data. The disadvantage of this approach is  
that such a large number of input neurons and the  
15 corresponding large number of total neurons and  
interconnections would result in a neural network that  
is very complex and expensive. Further, such a complex  
network takes a greater period of time to process  
information and to learn.

Thus, it would be desirable to provide a  
20 processor for classifying time-varying data with a  
minimum of preprocessing and requiring a minimum of  
algorithm and software development. It would also be  
desirable to provide a classification processor that is  
not based on explicit assumptions but instead can adapt  
25 by training to recognize patterns. It would also be  
desirable to provide a means for representing  
time-varying data to an adaptive processor in a  
simplified manner which reduces the total number of  
input values presented to the processor.

30 SUMMARY OF THE INVENTION

In accordance with the teachings of the  
present invention, an adaptive network is provided with  
at least  $N + 1$  input neurons, where  $N$  equals the number  
of values in a first domain associated with a given

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- 1 value in a second domain. The processor receives one of each of the  $N$  values in the first domain in the input neurons, and receives a single associated value from a second domain in the remaining input neuron.
- 5 The network is trained using known training data to produce an output that serves to classify the known data. The network training is repeated for each value in the second domain by presenting that value together with each of the  $N$  values in the first domain as input.
- 10 Once trained, the adaptive network will produce an output which classifies an unknown input when that input is from a class the adaptive network was trained to recognize.

BRIEF DESCRIPTION OF THE DRAWINGS

15 The various advantages of the present invention will become apparent to those skilled in the art after reading the following specification and by reference to the drawings in which:

20 FIG. 1 (A-D) are representative doppler signatures from four classes of multiple moving objects;

FIG. 2 is a diagram of the adaptive network in accordance with the teachings of the present invention; and

25 FIG. 3 is a representation of doppler data for four classes of objects; and

FIG. 4 is a drawing of an additional embodiment of the present invention.

DESCRIPTION OF THE PREFERRED EMBODIMENT

30 In accordance with the teaching of the present invention, a method and apparatus is provided for classifying two-dimensional data. The two-dimensional data can be derived from a variety of

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1 signal sources such as infrared, optical, radar, sonar, etc. The data may be raw, that is unprocessed, or it may be processed. One example of such processing is doppler processing, wherein the difference in frequency  
5 between an outgoing and an incoming signal is analyzed. In general, if the object reflecting the transmitted energy back is stationary with respect to the source there will be no shift in frequency observed in the returning energy. If the object is moving toward the  
10 source, the reflected energy will have a higher frequency, and if the object is moving away, the reflected energy will be lowered in frequency.

In FIGS. 1(A-D) four doppler signatures from four different classes of objects are shown. In these  
15 figures the doppler frequency, that is, the shift in frequency in the returning object or objects is represented along the horizontal axis. Time is represented along the vertical axis. It can be seen that FIGS. 1(A-D) each have a characteristic shape or  
20 pattern. The fact that the pattern changes from the lower portion of each figure to the upper portion, indicates changes in the detected doppler frequencies over time. This would indicate changes in the motion of multiple objects in the particular instance for each  
25 of the four classes of objects.

It should be noted that two different instances of multiple objects within a given class will have a doppler signature which resembles, but is not exactly identical, to each other. Thus, while it may  
30 be relatively easy for an observer, upon visual inspection, to identify a doppler signature from a given class, because of the subtle variations from instance to instance within a different class, it is difficult, if not impossible, for conventional  
35 processors to correctly identify the class of a doppler

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1 signature. For this reason the pattern recognition  
capabilities of a neural network would seem to be well  
suited to solving the doppler time signature  
classifying problem. However, one problem that is  
5 encountered is that due to practical limitations in the  
number of neurons in working neural networks, it would  
be difficult to provide a neural network with all of  
the information contained in the doppler signatures  
shown in FIGS. 1(A-D). To simplify the information,  
10 one could compress the data to its most essential  
characteristics. In this way, the data would be  
reduced to manageable proportions for processing by a  
neural network.

Accordingly, In FIG. 3 there is shown a  
15 representative simplified doppler signature for four  
different classes of objects. As in FIGS. 1(A-D), the  
horizontal axis represents the doppler frequency and  
the vertical axis represents time. Each horizontal  
line 10 in FIG. 3 represents the doppler frequencies  
20 received at a given time. There are 32 horizontal  
lines in FIG. 3, each representing a time slice of the  
doppler signal. The doppler signals in FIG. 3 are  
divided by means of vertical lines into four classes; a  
first class 12, a second class 14, a third class 15 and  
25 a fourth class 18. Like the four classes shown in  
FIGS. 1(A-D), the four classes in FIG. 3 represent  
doppler signals from four different types of objects  
and each have a pattern that is characteristic of that  
object, or objects. Even though FIG. 3 represents much  
30 more simplified doppler data than that shown in FIGS.  
1(A-D), representation of the four patterns in FIG. 3  
to a neural network would still involve a large amount  
of data. In particular, each time slice 10 in each  
35 class is drawn from doppler frequencies from 16  
frequency bins. There are 32 time slices 10 for each

1 class. Consequently, there would be 512 individual  
pieces of information for each class. Using  
conventional neural network techniques, a neural  
network having 512 input neurons might be required to  
5 process all of the information in each class shown in  
FIG. 3.

In order to simplify the representation of  
this data for presentation to the neural network, in  
accordance with the present invention, the data shown  
10 in FIG. 3 may be represented as indicated by FIG. 2.  
In FIG. 2 an adaptive network 20 in accordance with the  
preferred embodiment of the present invention is shown.  
The adaptive network 20 utilizes a conventional neural  
network architecture known as a multilayer perceptron.  
15 It will be appreciated by those skilled in the art that  
a multilayer perceptron utilizes a layer of input  
neurons 22, one or more layers of inner neurons 24 and  
a layer of output neurons 26. Each neuron in each  
layer is connected to every neuron in the adjacent  
20 layer by means of synaptic connections 27, but neurons  
in the same layer are not typically connected to each  
other. Each neuron accepts as input either a binary or  
a continuous-valued input and produces an output which  
is some transfer function of the inputs to that neuron.  
25 The multilayer perceptron shown in FIG. 2 may be  
trained by the conventional back propagation technique  
as is known in the art. This technique is described in  
detail in the above-mentioned article by D. E.  
Rumelhart and J. L. McClelland, which is incorporated  
30 herein by reference.

In accordance with the present invention the  
adaptive network 20 is configured so that it has a  
particular number of input neurons 22 determined by the  
input data. In particular, in the example in FIG. 2,  
35 the doppler data contains seven frequency bins. It

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1 will be appreciated that, for example, in FIG. 3 there  
will be 16 frequency bins, and that the number of  
doppler frequency bins will depend on the particular  
data to be analyzed, and the desired complexity of the  
5 adaptive network 20.

The doppler frequency curve 28, like the  
doppler frequency curves in FIG. 3, represents one time  
slice of doppler data. That is, it represents the  
10 doppler frequencies received at a given time. It is  
preferred that the range of frequencies be normalized  
so that they may be represented by a signal within a  
range that is acceptable to the input neurons 22. For  
example, the doppler frequencies may be normalized to  
have particular relative values between zero and one.

15 As shown in FIG. 2, seven input neurons each  
receive a single doppler frequency value from the  
doppler frequency curve 28. An eighth input neuron 30  
receives a signal which is representative of the time  
at which the doppler frequency curve 28 was received.  
20 The magnitude of the signal used for the time input  
neuron 30 may be normalized so that the entire range of  
time values falls within the acceptable range for the  
input neuron 22. For example, in the data from FIG. 3  
there are 32 doppler frequency curves from 32 different  
25 time slices and these times may simply be numbered 1  
through 32 wherein the range 1 through 32 is normalized  
for the signal transmitted to input neuron 30. When  
the doppler frequency curve 28, together with the time  
is transmitted to the input neurons 22 and 30, the  
30 adaptive network 20 will produce some output state at  
its output neurons 26. To train the adaptive network  
20 to produce a desired output, the learning algorithm  
known as backward error propagation may be used. In  
this technique a known doppler frequency and time input  
35 will be presented to the input neurons and the adaptive

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1 network 20 will be trained to produce an output  
corresponding to the class of the doppler frequency  
curve. For example, assuming that the training input  
is from a first class, the desired output may be to  
5 have the first two output neurons 26 produce binary  
ones and all the other output neurons produce binary  
zero values. After repeated training procedures the  
adaptive network 20 will adapt the weights of the  
synaptic connections 27 until it produces the desired  
10 output state. Once the adaptive network 20 is trained  
with the first doppler frequency curve 28 at a first  
time slice, it may then be trained for all the  
successive time slices. For example, the adaptive  
network 20 may be trained for each of the 32 doppler  
15 frequency curves 10 in FIG. 3 to produce an output  
indicating the first class. Once the training for the  
first class is complete, an unknown set of doppler  
frequency curves and times may be transmitted to the  
adaptive network 20. If the unknown doppler signature  
20 has the general characteristics of that of the first  
class, the adaptive network 20 will produce an output  
state for each time slice corresponding the first  
class.

Further, the adaptive network 20 may be  
25 trained to recognize multiple classes of doppler  
signatures. To accomplish this, the steps used to  
train the adaptive network 20 to recognize the first  
class of doppler frequency curves is simply repeated  
for the second, third and fourth classes. As shown in  
30 FIG. 2, the adaptive network 20 may be trained to  
indicate the second, third and fourth classes by  
producing binary ones in the output neurons 26  
associated with those classes as indicated in FIG. 2.  
The number of classes which the adaptive network 20 may  
35 be trained to recognize will depend on a number of

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1 variables such as the complexity of the doppler signals, and the number of neurons, layers and interconnections in the adaptive network 20.

5 Referring now to FIG. 4, an adaptive network 20 in accordance with the present invention is shown. This embodiment is similar to the one shown in FIG. 2, except that it utilizes 18 input neurons 22, 24 inner neurons 24 and 26 output neurons 26. It will be appreciated that with a larger number of neurons and 10 synaptic connections 27, time-varying data of greater complexity can be classified.

15 Once the adaptive network 20 has been trained it could be reproduced an unlimited number of times by making a copy of the adaptive network 20. For example the copies may have identical, but fixed weight values 15 for the synaptic connections 27. In this way, mass production of adaptive networks 20 is possible without repeating the training process.

20 In view of the foregoing, those skilled in the art should appreciate that the present invention provides an adaptive network that can be used in a wide variety of applications. The various advantages should become apparent to those skilled in the art after having the benefit of studying the specification, 25 drawings and following claims.

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CLAIMS

what is Claimed is:

1           1. An information processor (20) for  
classifying a set of two-dimensional data, said data  
representing information from at least two domains,  
including a first and second domain, said information  
processor including a network of neurons including  
5           input (22) and output (26) neurons, there being at  
least  $N + 1$  input neurons, a plurality of synaptic  
connections (27) providing weighted interconnections  
between selected ones of said neurons, characterized  
10          by:

              said network (20) having at least  $N + 1$  input  
neurons (22), where  $N$  is the number of values in said  
first domain;

15          means for transmitting a set of input signals  
to said input neurons (22), each signal being received  
by at least one input neuron, said set of input signals  
including at least a single value from said second  
domain, and said set of input signals also including  $N$   
values from said first domain, said  $N$  values all being  
20          associated with said single value in said second  
domain; and

              means for training (22, 24, 26) said network  
(20) to produce a desired output including means for  
presenting a known input signal to said input neurons  
25          (22, 30), and means for adjusting (24, 26) said  
weighted synaptic interconnections (27) in repeated  
training sessions to cause said network (20) to produce  
said desired output.

1           2. The information processor (20) of Claim  
1 wherein said second domain is time, and the  $N$  values  
from the first domain associated with a given time  
value represents the values of those  $N$  values at a  
5          given time.

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1                   3. The information processor of Claim 2  
wherein said second domain represents doppler data.

1                   4. The information processor of Claim 3  
wherein said classification represents different types  
of objects from which said doppler signals originate.

1                   5. The information processor of Claim 1  
wherein the total number of input neurons (22) is  $N + 1$ .

1                   6. The information processor of Claim 1  
wherein said desired output represents a classification  
for a plurality of said known input signals.

1                   7. The information processor of Claim 1  
wherein said means for training said network (24, 26)  
trains said network with multiple input signals that  
include a plurality of inputs from the second domain  
5                 along with the associated  $N$  inputs from the first  
domain.

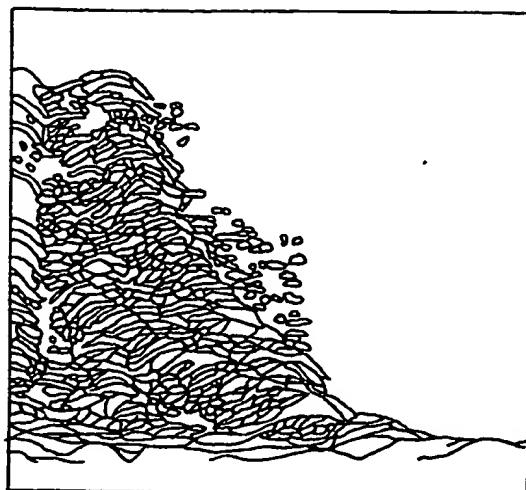


Fig-1A

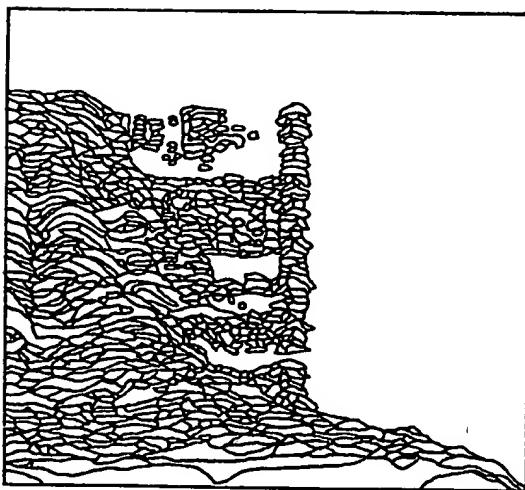


Fig-1B

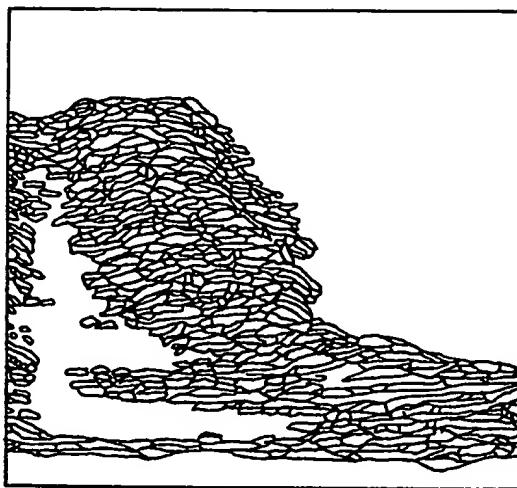


Fig-1C

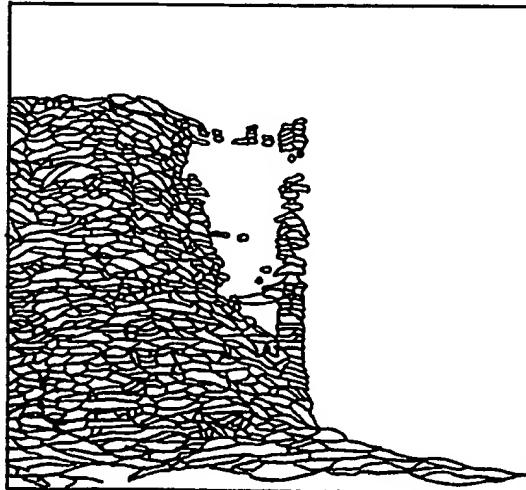


Fig-1D

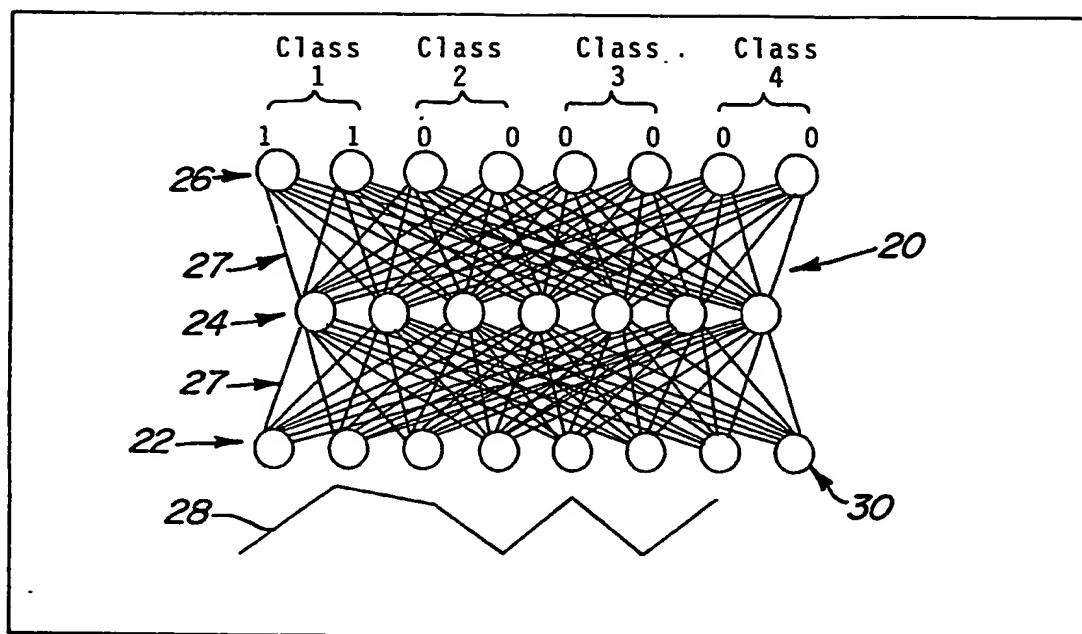


Fig-2

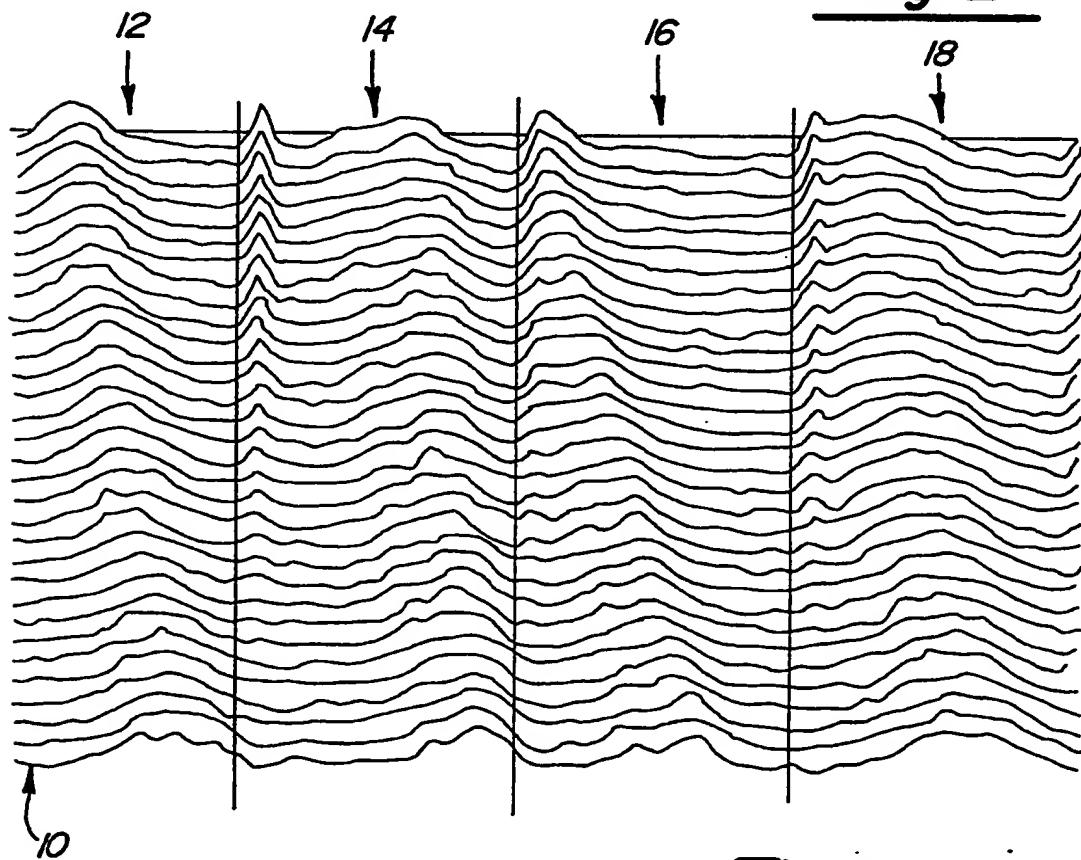
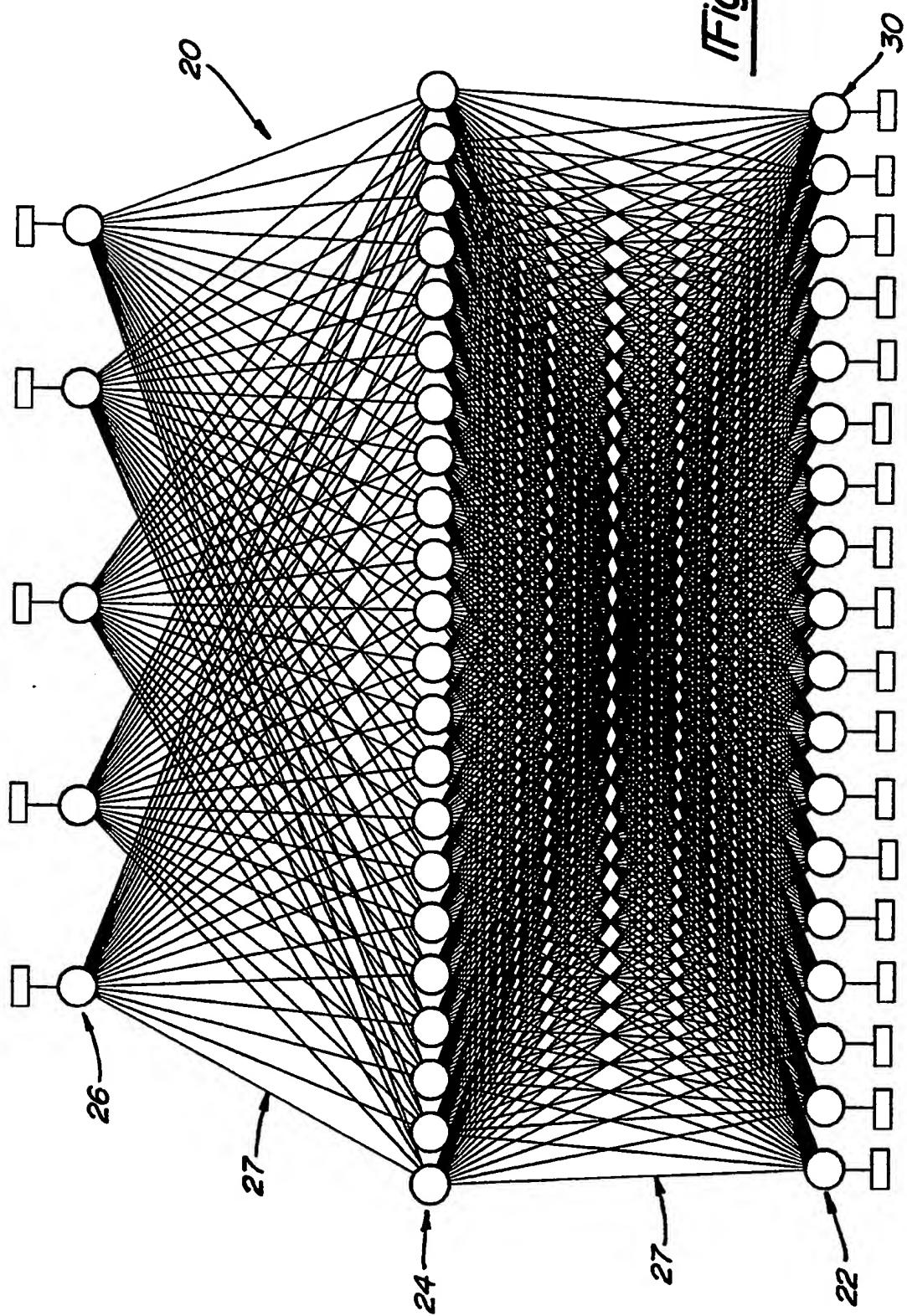


Fig-3

Fig-4



# INTERNATIONAL SEARCH REPORT

International Application No PCT/US 90/04487

## I. CLASSIFICATION OF SUBJECT MATTER (if several classification symbols apply, indicate all) \*

According to International Patent Classification (IPC) or to both National Classification and IPC

IPC<sup>5</sup>: G 06 F 15/80, G 01 S 7/02

## II. FIELDS SEARCHED

Minimum Documentation Searched ?

| Classification System   | Classification Symbols    |
|---|---------------------------|
| IPC <sup>5</sup>  | G 06 F 15/80, G 01 S 7/02 |
| Documentation Searched other than Minimum Documentation to the Extent that such Documents are Included in the Fields Searched * |                           |

## III. DOCUMENTS CONSIDERED TO BE RELEVANT\*

| Category * | Citation of Document, <sup>11</sup> with indication, where appropriate, of the relevant passages <sup>12</sup>  | Relevant to Claim No. <sup>13</sup> |
|------------|---|-------------------------------------|
| X          | IEEE International Conference on Neural Networks, San Diego, California, 24-27 July 1988, P.F. Castelaz: "Neural networks in defense applications", pages 473-480<br>see page 476, lines 10-31; figure 2<br>--  | 1-7                                 |
| A          | IJCNN International Joint Conference on Neural Networks, Sheraton Washington Hotel, 19-22 June 1989, A. Khotanzad et al.: "Target detection using a neural network based passive sonar system", pages I-335-I-340<br>see abstract; page I-336, column 1, lines 15-32; column 2, lines 30-36; pages I-337, column 1, lines 1-31; column 2, lines 35-49; figure 2<br>-- | 1-7                                 |
|            | . / .   |                                     |

\* Special categories of cited documents: <sup>10</sup>

- "A" document defining the general state of the art which is not considered to be of particular relevance
- "E" earlier document but published on or after the international filing date
- "L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)
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"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art.

"&" document member of the same patent family

## IV. CERTIFICATION

Date of the Actual Completion of the International Search  
13th November 1990

Date of Mailing of this International Search Report

- 4. 12. 90

International Searching Authority

Signature of Authorized Officer

EUROPEAN PATENT OFFICE



M. PEIS

## III. DOCUMENTS CONSIDERED TO BE RELEVANT (CONTINUED FROM THE SECOND SHEET)

| Category * | Citation of Document, <sup>15</sup> with indication, where appropriate, of the relevant passages   | Relevant to Claim No. |
|------------|--|-----------------------|
| A          | IEEE First International Conference on<br>Neural Networks, San Diego,<br>California, 21-24 June 1987,<br>H. Boulard et al.: "Multilayer<br>perceptrons and automatic speech<br>recognition", pages IV-407-IV-416<br>see page IV-413, lines 3-20, page<br>IV-414, lines 1-13; figure 2<br>----- | 1-7                   |